Chapter 16

Collective Intelligence and Adaptation

The concept of collective intelligence is central to the development of multi-agent systems(MAS), drawing inspiration from biological and societal cooperation. An inherent concept within collective intelligence is the “Wisdom of Crowds” by [915], which asserts that independent communities often make better decisions as a whole than any one person. Cognitive theoretical models like the Society of Mind [17] and its related theory mind [916, 917] further support the paradigm, suggesting that intelligence springs from a synergy among primary, specialist components. Moreover, In human societies, individuals collaborate, divide labor, and engage in collective problem-solving to address complex challenges. MAS adopt similar strategies where specialized agents to participate in solving complex problems and collective decision-making [914].

The emergence of collective intelligence within MAS is a dynamic and iterative process. Through continuous interaction, agents develop a shared understanding and collective memory progressively. The interaction dynamics are strengthened by heterogeneity among individual agents, environmental feedback, and agent-agent interactions [914], which are all important for the emergence of complex social networks and improving decision-making strategies. It is worth highlighting that collective intelligence is not merely the summation of individual capability, but refers to emergent behavior beyond individual agent capacity. beyond individual agent capacity. Individual agent development is deeply linked with collective intelligence growth. With ongoing involvement with collective tasks, and self-reflection on shared contexts, agents increasingly develop reasoning and decision-making capabilities. The evolution of individual agents is closely related to collective intelligence evolution. Through continuous interaction in joint activities and critical examination of shared contexts, agents continuously refine their reasoning and decision-making abilities.

In parallel, complex and diverse behavior among agents emerges. These include beyond-restricted-protocol behaviors, such as advanced social interactions, including trust, strategic deception, adaptive camouflage, and emergent cooperation, evoking a shift from reactive into cooperative strategies, as well as deeper social dynamics. With a chain of recursive interactions, agents necessarily form cooperative strategies, which eventually turn into social contracts, organizational hierarchies, and divisions of labor. Social phenomena necessarily emerge through recursive interactions among agents, coupled with their adjustment with the changing environment. It marks a transition from fundamental cooperative behavior into complex social constructs, leading to cultural norms and conventions.

16.1 Collective Intelligence

The concept of collective intelligence, which refers to the ability of a group of agents to exhibit problem-solving capabilities that surpass those of individual agents. This phenomenon is often characterized by emergent behaviors, sophisticated decision-making, and higher-order reasoning abilities that arise from interactions among agents, leading to enhanced performance in collaborative decision-making scenarios and social simulations [975]. [917] demonstrate that LLM-based agents can exhibit collaborative behaviors and high-order Theory of Mind capabilities, which are crucial for understanding the perspectives of other agents in a shared environment. Their findings suggest that the integration of LLMs into MAS can facilitate more sophisticated forms of collective intelligence, thereby improving the overall efficacy of collaborative decision-making.

Improved System Performance A primary advantage of collective intelligence in MAS is that collaboration leads to superior problem-solving capabilities. Collective intelligence can be encouraged to overcome “groupthink” and individual cognitive bias in order to allow a collective to cooperate on one process – while achieving enhanced intellectual performance. When individual agents share information and coordinate actions, the system can achieve better results than any single agent operating independently [626, 922, 1046, 1031, 1063]. Collective intelligence is therefore shared or group intelligence that emerges from the collaboration, collective efforts, and competition of many individuals and appears in consensus decision making. Collective intelligence strongly contributes to the shift of knowledge and power from the individual to the collective. [924] demonstrated this through their Cooperative Embodied Language Agent (CoELA), which achieved a 40% improvement in efficiency over traditional planning methods in ThreeDWorld multi-agent transport tasks. This substantial improvement stems from the system's ability to effectively utilize LLMs for planning and communication in multi-agent settings, providing compelling evidence for enhanced collaborative decision-making capabilities. As previously discussed, the inherent diversity and interdisciplinary nature of LLM-based multi-agent systems, along with various inter-agent interaction, which provide internal feedback and enriched context for individual decision-making, hence reduce bias and improve the consistency of solution [918].

Emergent Behaviors One of the most intriguing aspects of collective intelligence is the emergence of new, complex behaviors that arise spontaneously from agent interactions. These behaviors are not explicitly programmed but emerge from learning and adaptation. As discussed in various studies [971, 965, 966], agents developed strategic behaviors, including trust-building, adversarial tactics, deception, and leadership during the game. The collective behavior evolved through experience sharing, where village-aligned agents learned cooperation and strategic alliance formation, and wolf-aligned agents improved deception through "information confusion" tactics. Moreover, agents optimized voting patterns and deception strategies without explicit training, which indicates the group intelligence emerged over multiple rounds of interactions. Similarly, in the Avalon game [968], researchers observed that agents became better at identifying and countering deceptive information. Individuals adapted to deceptive environments and refined their decision-making using first- and second-order perspective shifts. Furthermore, agents demonstrated adaptive cooperation and ad hoc teamwork, despite no predefined collaboration protocols [969]. These findings highlight the ability of LLM-based agents to develop sophisticated behaviors through interaction and learning, showcasing the potential for emergent behaviors in collective intelligence scenarios. Notably, these emergent behaviors rely on memory and reflective mechanisms. Agents retrieve and reflect on historical information to generate a compact context, enhancing their reasoning capabilities [239]. In MAS, shared context and environmental information significantly boost agents' usable memory. This enables agents to build on past interactions, refine strategies, and adapt more effectively to dynamic environments [1064].

Social Evolution One of the most significant findings in the field of generative agent societies is the spontaneous emergence of social norms. [1065] demonstrated that agents, through continuous interaction, are capable of creating, representing, spreading, evaluating, and complying with social norms. These norms serve as the foundation for social order, reducing conflicts and improving coordination among agents, thereby leading to more stable and organized societies. Interestingly, the study found that agents develop norms more rapidly in their beliefs than they do in their behaviors. This suggests that while agents may quickly internalize certain norms, the translation of these norms into consistent actions takes longer. Over time, these norms tend to synthesize into more general principles, resulting in more concise and effective personal norm sets. Furthermore, the Project Sid simulation[989] models large-scale agent societies and provides further evidence of the emergence of social norms and role specialization. In this study, agents were observed to autonomously form specialized social roles. These roles were not predefined but emerged naturally as agents interacted within their environment and developed collective rules.The simulation also highlighted the importance of democratic processes in the adherence and modification of these collective rules. Agents were found to engage in cultural and religious transmission, spreading ideas and doctrines across communities. This process of norm creation and role specialization leads to better organization, reduced conflict, and adaptive governance structures within the society. The evolution of cultural and religious beliefs in multi-agent societies is also observed in [1066], which occurs through agent-driven selection of ideas, mirroring real-world societal changes. Additionally, the [936], which simulates social interactions among one million agents, provides valuable insights into cultural transmission and group polarization. Cultural memes and belief systems propagate naturally among agent societies. Agents exhibit herd behavior, conforming to prevailing opinions even when these opinions are irrational. This leads to the emergence of group polarization, where agents reinforce extreme views through repeated interactions. This finding highlights the significant impact of group size on the dynamics of cultural evolution and social behavior.

16.2 Individual Adaptability

In multi-agent systems (MAS), individual adaptability refers to an agent's ability to adjust its behavior and decision-making strategies based on previous interactions and experiences. This is also defined as self-evolving, where agents can dynamically self-evolve by modifying themselves, such as altering their initial goals and planning strategies, and training themselves based on feedback or communication logs [38]. This adaptability is facilitated by the integration of large language models (LLMs), which support dynamic monitoring and adaptation processes [1067], as well as the agents' memory capabilities and information exchange. These modules are crucial to ensure that agents can continuously improve their performance, respond effectively to dynamic environments, and optimize their decision-making processes. We categorize the mechanisms contributing to individual adaptability into memory-based learning and parameter-based learning, where there are training-free and training-based approaches.

Memory-based learning Memory and reflective mechanisms significantly enhance individual adaptability in LLM-based multi-agent systems by leveraging historical records and experiences to inform decision-making [221, 1068, 50]. By maintaining and utilizing individual memory of past interactions, decisions, and outcomes, the agent can refine its decision-making process over time. This memory serves as a repository of experiences that the agent can draw on when making future decisions. Using this stored knowledge, individual agent is able to refine its decision-making process, learning from previous successes and failures [921, 1051]. For example, in clinical simulation, doctor agents can keep improving treatment performance over time by accumulating experience from both successful and unsuccessful cases [921]. In social behavior simulation, agents can improve their adaptability by engaging in more complex scenarios and utilizing scenario memories to enhance performance [50].

Shared memory-based learning In contrast, shared memory-based learning extends this concept by enabling multiple agents to exchange information and insights derived from their respective experiences. Rather than relying solely on individual memory, agents can benefit from the collective knowledge of the group. By sharing data, strategies, and feedback, agents enhance their ability to cooperate and optimize their decisions collaboratively. Shared memory-based learning is particularly valuable in environments where agents need to cooperate, exchange tasks, or work toward common goals [919, 967, 968]. For instance, ProAgent [1069] anticipates teammates' decisions and dynamically adjusts each agent's strategies based on the communication logs between agents, facilitating mutual understanding and improving collaborative planning capability.

Parameter-based learning. Beyond memory-based learning in textual form, many MAS employ parameter-based learning, which evolves agents' individual adaptability through post-training techniques. For instance, [1070] discusses thea Learning through Communication (LTC) paradigm, whereusing communication logs between agents are leveraged to constructto generate datasets forto training or fine-tuninge LLMs. The integration of symbolic and connectionist paradigms within LLM-powered agents enhances botheir reasoning and adaptability. More recently, research has increasingly focused on multi-agent (co-)fine-tuning, which improves collaboration and reasoning capabilities through cooperative trajectories. Examples include multi-agent debate fine-tuning [1071] and SiruiS [1072]. Additionally, Sweet-RL [1073] employs reinforcement learning to enhance the critic model within MAS, fostering better collaborative reasoning. However, despite their promising performance, future parameter-based learning paradigms may need to address the balance between agents' general capabilities and their specialization for specific roles within MAS.This hybrid approach allows agents to handle both structured and unstructured data, improving their ability to make decisions in dynamic environments [1074, 1075].